

Digital pathology annotation & image quality assessment platform for developing and training various AI cancer models and realizing the intelligent clinical assessment

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Introduction

AI-driven computational pathology diagnosis is an emerging but rapidly growing field. It applies computational algorithms such as artificial intelligence and machine learning solutions to classify cancer and other diseases from digital pathology images. A high-quality database of digital pathology images and labels (called annotations) are fundamental to the development of AI-based solutions. Annotations requires proper pathology training by experienced pathologists because most successful models are based on supervised learning. Specific regions/structures must be labeled and annotated to describe the disease, and then a learning model can be built. However, the limited number of trained pathologists and the high clinical workload make it difficult to obtain extensive, systematic and structured digital pathology image annotation datasets to develop accurate supervised learning models. To make matters worse, the quality of digital pathology images is almost impossible to quantitatively assess with the naked eye, and about 15% of digital pathology images have quality problems. To address this, we have developed AimagQC, a fully automated Histology Image Quality Assessment tool. Histology Laboratory can easily integrate AimagQC within their workflow in between image acquisition and analysis. To facilitate advances in computational pathology, cloud-based structural annotation platforms (AIHistoNotes) were developed to enable pathologists to select high-quality digital pathology images for annotation. Based on this cloud-based solution, we are building an annotation dataset for prostate cancer, linking annotations with ontology information to enable accurate pathological diagnosis based on artificial intelligence. As a result, clinical validation and decision-making by pathologists can be faster, easier, and more accurate. Here, we demonstrate this platform to facilitate prostate cancer diagnosis using H&E images. In the future, we will expand this platform to other cancer types.

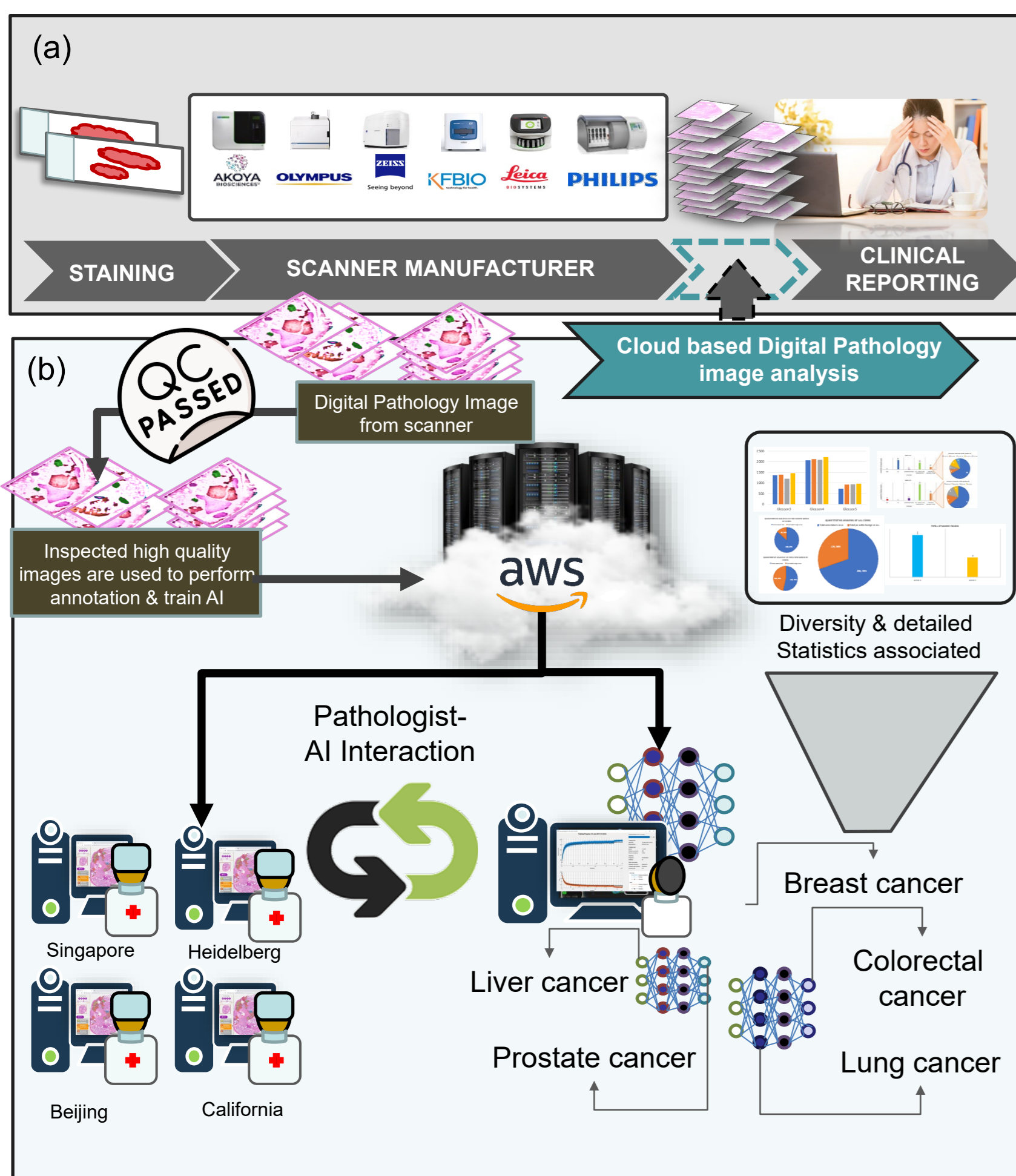
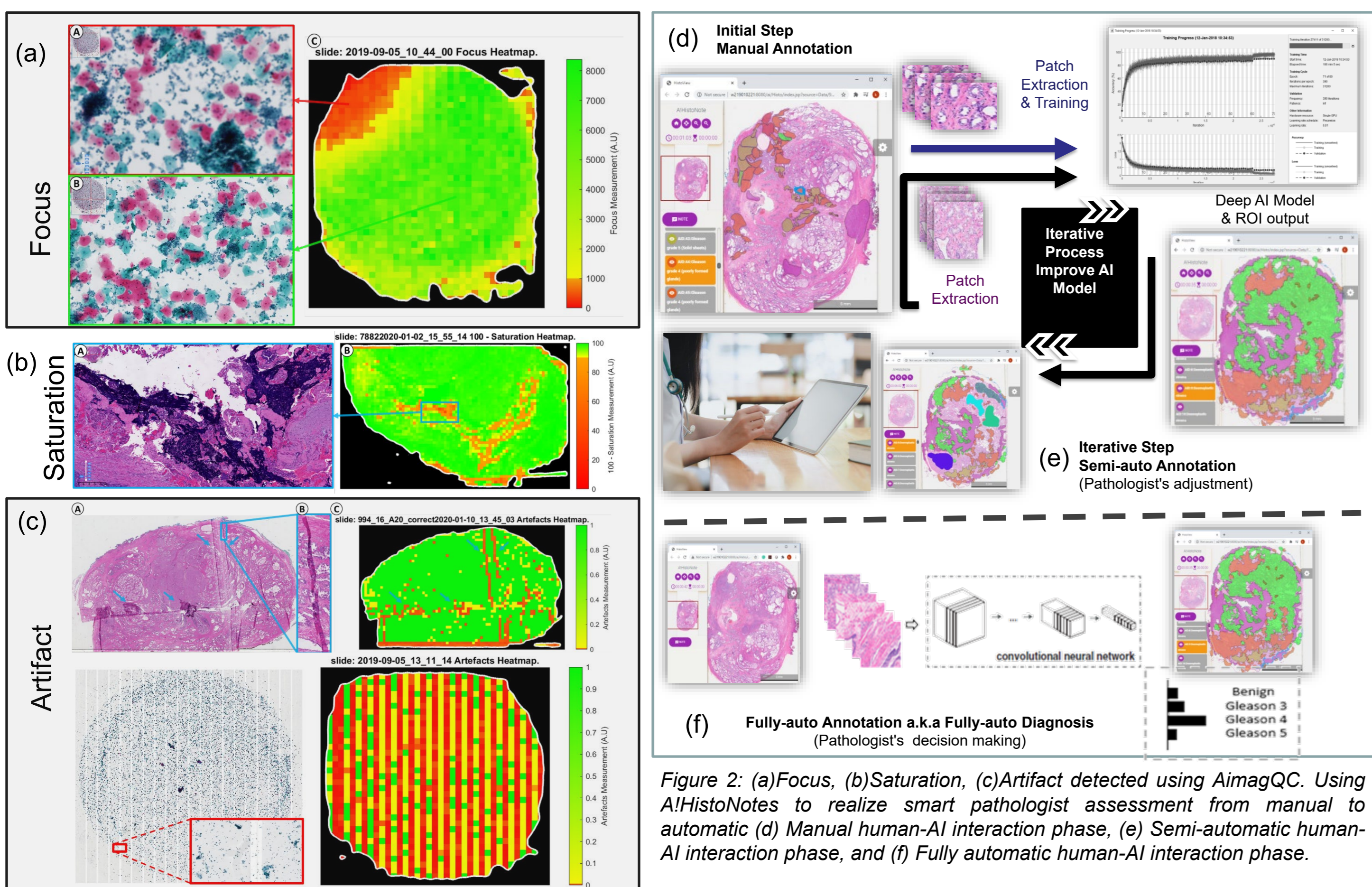


Figure 1: (a) Existing digital pathology assessment pipeline and (b) Cloud based digital pathological image analysis with automatic assessment pipeline.

Methods

With the adoption of modern digital solutions in the practice of everyday pathologists, automated quality assessment tools are especially important because they can effectively distinguish the source of common artifacts observed in digital images. The following steps can be taken when the quality of a digital slide is assessed to be below an acceptable quality level. Artifacts such as tissue tears, folds, air bubbles, over/under staining are associated with tissue sample preparation and should therefore be sent for re-cutting. Out of focus, image contrast and saturation, tiling are related to scanning issues, so samples should be sent for rescanning. We approach the Quality of the Tissue at a local level using a parallel analysis of Tiles of 256*256 pixels throughout the Region of Interest (i.e. Tissue Detected). The overall quality of a Tissue Image can be assessed using a weighted average of five features. Such as Focus (Fig. 2a), Contrast, Saturation (Fig. 2b), Artifacts (Fig. 2c), and Texture Uniformity.



AIHistoNotes aims to build a bridge between humans and artificial intelligence, enabling pathologists to effectively "communicate" with AI. The annotated region of interest (ROI) is a kind of "communication" tool on this platform, so that people can directly understand the output and suggestions of AI. In the same situation, the ROI annotated by the pathologist will be converted into digital information that AI can understand. In this way, communication and exchanges between the two parties can be truly realized as shown in Fig. 1b. The process of using AIHistoNotes in the interaction between humans and AI is divided into three important phases. They are the manual human-AI interaction phase, the semi-automatic human-AI interaction phase, and the fully-automatic human-AI interaction phase shown in Figures 2d, 2e, and 2f.

Main challenge for the development of digital pathology AI

- Lack of comprehensive quality control (QC) solution & not possible inspected by naked eye.
- ~15% of the WSI images are problematic
- Lack of annotations for abnormal tissues, such as tumour regions and their histological subtypes.
- Many of these images are not annotated and verified using standard procedures.
- Annotating tumor regions and their histological subtypes is a tedious and time-consuming task for pathologists.

Objective

To propose and develop an automated digital pathology image quality assessment software (AimagQC) and validated smart annotation system (AIHistoNotes).

Expected research outcomes

- Enables pathologists to contribute and transfer their knowledge effectively to build AI detection and classification models.
- Quickly focus on cancer areas and quantify them.

Results

A total of 12,416 prostate cancer annotations were made on 188 prostate cancer images through the AIHistoNotes platform. In this example, five primary annotation labels are used for prostate biopsy screening and whole-section image (WSI) diagnostic studies. They are Stroma, Normal, Gleason grade 3, Gleason grade 4, and Gleason grade 5. The number of each annotation category can be seen in the pie chart in Figure 3a. Gleason grade 3 and Gleason grade 4 are a large number of annotations that have been created because they are important key indicators needed to correctly identify prostate cancer treatment. In Figure 3b, we can use AIHistoNotes to extract patch images from annotations for AI model training and validation. Also in Figure 3b, the Gleason grade by color. For example, green represents Gleason grade 3 and its corresponding patch can be observed. AIHistoNotes is used to extract region information from annotations to understand the average size of each class (Figure 3c). In addition, one of the features provided by AIHistoNotes is a time recorder. This means that the time each annotation was created will be logged. Therefore, we can generate a result in Figure 3d to study the speed and time of different annotation categories. For example, pathologists spend more time on Gleason 3 on average than Stroma. The likely reason is that Gleason grade 3 needs more attention when drawing edges. The results were 3 times faster when drawing the stroma, probably because it was easier for the pathologist to identify.

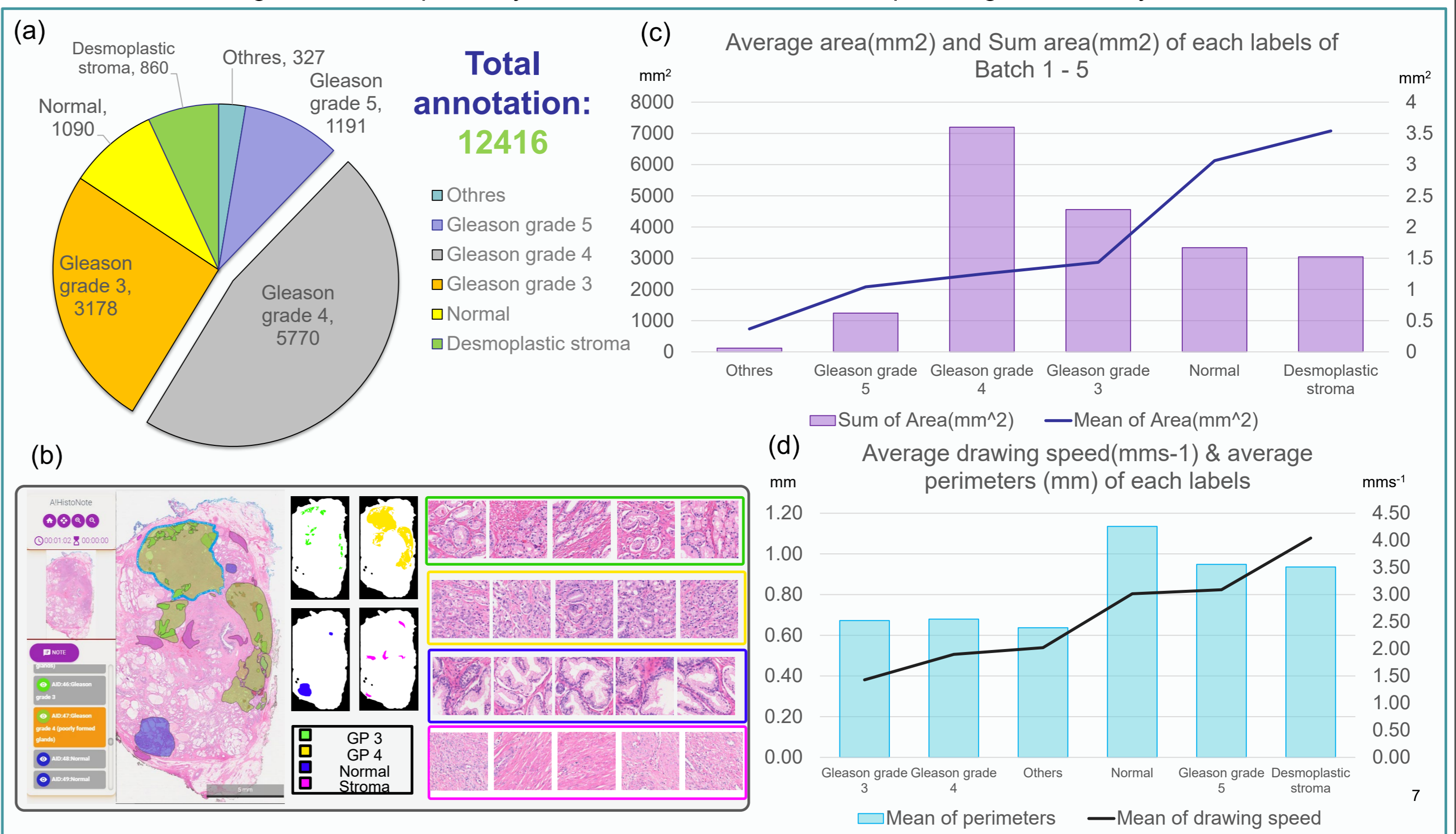


Figure 3: Analysis of pathologist's annotation performance using AIHistoNotes, where a) represents the total number drawn by pathologist, b) patch extraction corresponding to annotation drawn by pathologist, c) pathologist draws based on various labels, d) and the speed required to complete each label.

In the AIHistoNotes application it is easy to customize the design, for example, although the AI model can create hundreds of notes for the precise location of its corresponding graded area. This can make it difficult for pathologists to interpret the entire slide image. The human eye may not easily track and understand the number of each category, as shown in Figure 4a. This can slow down their assessment process and confuse pathologists' understanding of Gleason grades on images. Therefore, the number of annotations and accurate grade-specific annotations were custom designed based on pathologist feedback, as shown in Figure 4b.

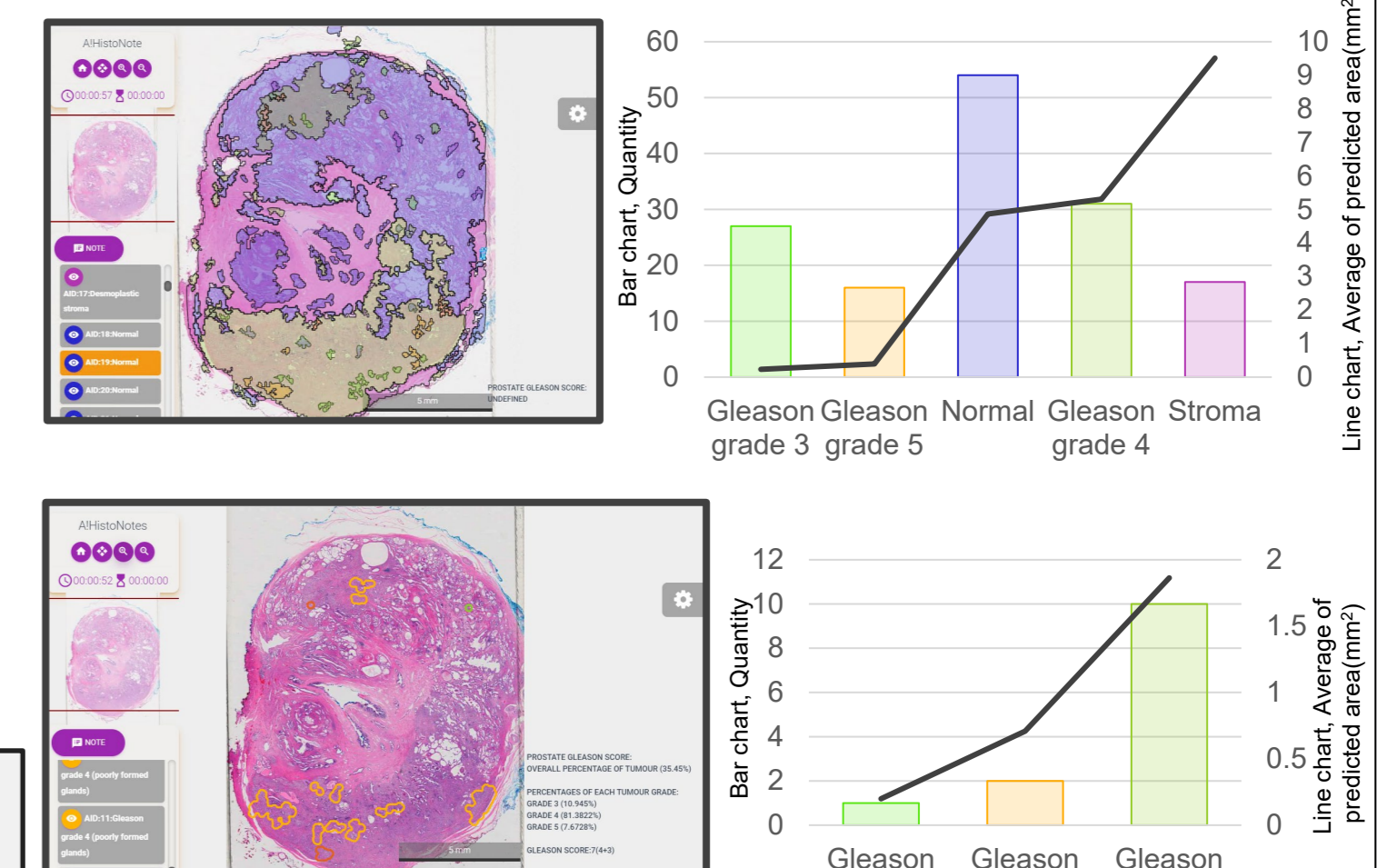


Figure 4: Quantity & Area of each Prostate region a) full prediction by AI, b) tailor-made prediction by AI

Since annotation quality and subsequent model development ultimately depend on the quality of the scanned WSI, it is critical to have a QA system that can accommodate changes in sample preparation and tissue type. Additionally, image appearance and quality can vary widely between scanners, resulting in differences in color, brightness, and contrast for the same sample. Various other brands of scanners may be used by different research laboratories, such as Olympus, Leica, KFBio, and Philips. Therefore, we used AimagQC to identify five common WSI quality problem categories in images acquired from various scanners: out-of-focus, low contrast, saturation, artifacts, and texture uniformity. We randomly selected 38 prostatectomy specimens from the prostate study sample and scanned them with 5 other scanners and assessed them with AimagQC. Figure 5 shows the feature evaluation of the scanned images from different scanners in this study and their impact on the performance of the AI model.

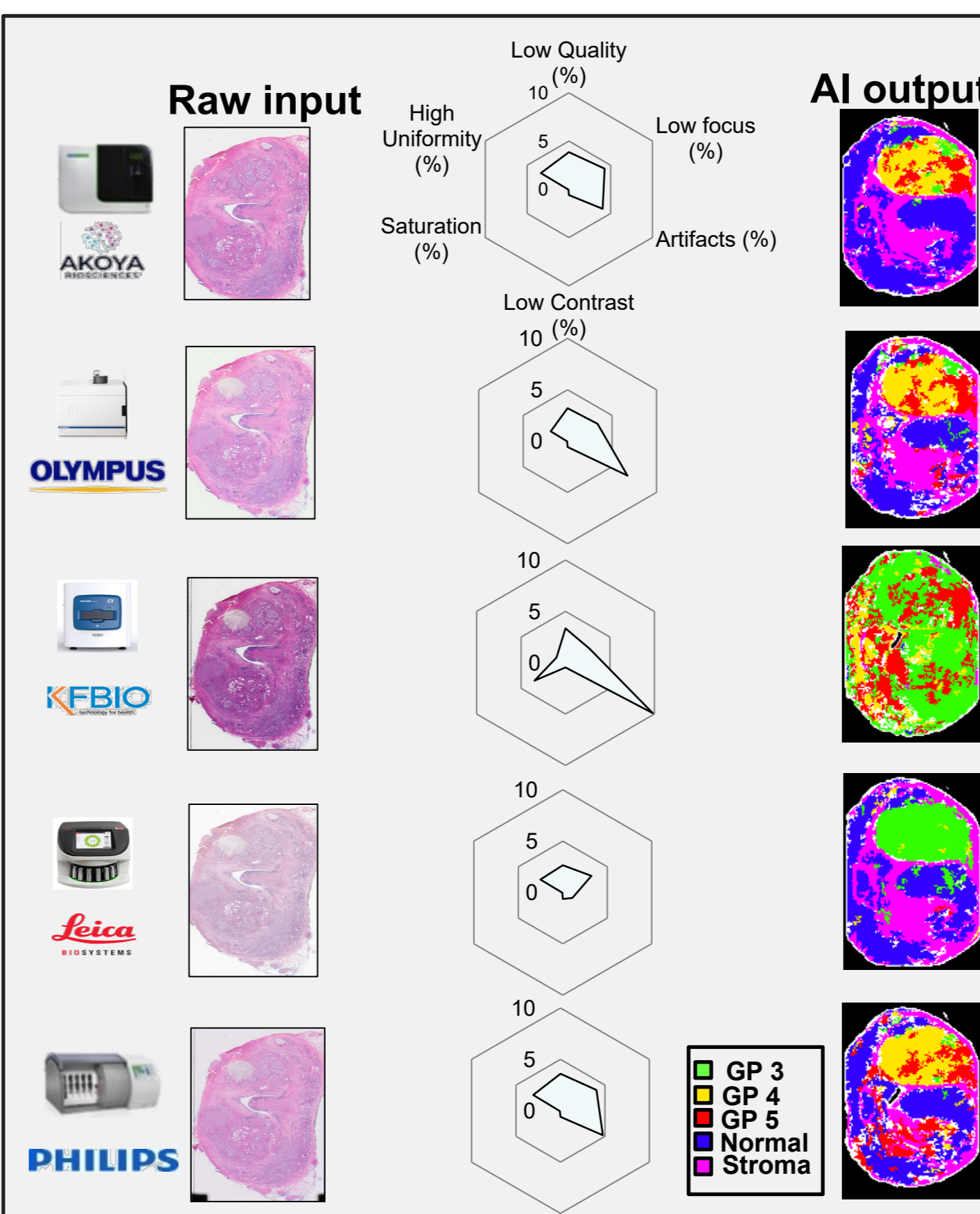


Figure 5: Image quality analysis of raw image output from various common brands of scanners using AimagQC and the corresponding quality impact when detected with AI models.

Conclusions

AI detection and classification models equipped with pathologist-AI interaction systems are a popular trend in the field of digital pathology images. This will bring new developments to current histopathology workflows. In this work, we demonstrate that the application of AimagQC and AIHistoNotes in prostate cancer is an important milestone. The AimagQC solution can quickly identify poor quality image data to be rescanned before pathologists manually evaluate and train AI models. Notably, AimagQC can be integrated post imaging in a modern Digital Pathology Lab Workflow. Furthermore, it can also be directly integrated within main microscope providers. AIHistoNotes' annotation viewer and tools integrated with AI models can help pathologists identify and classify cancer areas quickly and efficiently. Therefore, it significantly reduces the burden of pathology workload, especially in third world countries where there is a shortage of pathologists. The proposed solution indirectly benefits the public. For example, cancer cases can be detected in a relatively short period of time, reducing delays in proper diagnosis and treatment. We also demonstrate that the concept of pathologist-AI interaction is feasible and contributes to the development of digital pathology computing and pathology diagnostic procedures. Therefore, the proposed platform is likely to perform and train machine learning in other types of cancer in the near future.

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